# A JOINT FRAMEWORK FOR ANALYSIS OF AGRI-ENVIRONMENTAL PAYMENT PROGRAMS

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This article presents an approach for simultaneously estimating farmers' decisions to accept incentive payments in return for adopting a bundle of environmentally benign best management practices. Using the results of a multinomial probit analysis of surveys of over 1,000 farmers facing five adoption decisions in a voluntary program, we show how the farmers' perceptions of the desirability of various bundles change with the offer amounts and with which practices are offered in the bundle. We also demonstrate an estimator for the mean minimum willingness to accept for the adoption of a practice conditional on the cost share offers for other practices.

*Key words*: best management practices, EQIP, incentive payments, multinomial probit, simulated maximum likelihood estimation, simulated multivariate normal, WTA.

Agri-environmental payment programs play an important part in improving the environmental performance of agriculture (Claassen and Horan, Batie, Lynch and Smith, Smith; Feather and Cooper, Claassen et al.). Federal-level interest in developing these programs is currently strong. For example, the 2002 Farm Act calls for a five fold increase in funding for the USDA's Environmental Quality Incentives Program (EQIP). This article focuses on voluntary programs designed along the lines of the EQIP, which provides incentive payments to encourage producers to adopt environmentally benign land management practices such as nutrient management, manure management, and integrated pest management.

For policy-making purposes, it would be useful to know the sensitivity of the producer's decision to enroll in response to a schedule of potential incentive payments and to which practices are bundled together. Such information can be used to assess the costs of encouraging farmers to try various environmentally benign management practices (commonly known as best management practices, or BMPs).

EQIP offers the farmer a suite of BMPs to choose from. Existing published research (Cooper and Keim) modeled the probability of farmer adoption of BMPs as a function of the incentive payment, with each practice being modeled independently in a bivariate probit analysis of actual adoption and hypothetical adoption. Khanna also conducts a bivariate probit analysis of technology adoption, but between two technologies at a time.

Logically, there is no reason to believe that the farmer's decision to adopt each of these practices should be treated independently; these BMPs should be considered as a bundle of interrelated practices (Amacher and Feather). If each adoption decision is treated independently in estimation, then valuable economic information may be lost. If the available set of BMP options does indeed influence the farmer's decision as to which practices to adopt, then the adoption decision follows a multivariate distribution. The multinomial probit (MNP) model, which makes use of the multivariate normal (MVN) distribution, is the appropriate econometric tool for modeling multiple adoption decisions in a joint manner such that the correlations of the error terms across the practices are nonzero.

In the numerical illustration, a dataset drawn from surveys of over 1,000 farmers in four U.S. regions is used to simultaneously model five discrete choices in an EQIP-like cost-sharing program. This program offers cost shares only for practices that the farmer does not currently use. In the model presented here, farmers who do not use a desired practice are asked whether they would accept a hypothetical cost share offer to adopt the practice, and each hypothetical adoption decision is treated jointly. By modeling the decision-making

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process jointly across the offered BMPs, the resulting estimate of the correlations across the decisions allows us to examine those BMPs that the farmers consider to be bundles, and to calculate conditional probabilities and summary statistics. This information can be of policy significance in the design of the type of agri-environmental payment program discussed here. Before turning to the econometric model and then to the numerical illustration of the approach, in the next section we provide the theoretical basis for addressing the incentive payment program as a bundle of technologies to be adopted.

## The Theoretical Model

Consider a farmer who is faced with a set of decisions on what combination of $j = 1, \ldots, J$ BMPs to choose from under a incentive payment program. The farmer's discrete decision to accept incentive payments in exchange for adopting the BMPs can be modeled using the random utility model (RUM) approach (e.g. Hanemann).[1] From the utility-theoretic standpoint, a farmer is willing to accept a cost share $A_j$ per acre to switch to a new BMP $j$ if the observable portion of the farmer's indirect utility with the new practice and incentive payment, $V_{1j}(s, A_j, \varepsilon_1; \theta)$, is at least as great as at the initial state, $V_0(s, \varepsilon_0; \theta)$, i.e., the farmer's decision to adopt the practice can be expressed as $V_{1j} \geq V_0$, where 0 is the base state, 1 is the state with the green practice $j$ adopted, $s$ is a vector of explanatory variables, the error term $\varepsilon$ is an independently and identically distributed random variable with zero mean, and $\theta$ is a vector of the parameters of the functions. Say that $C_j$ is the cost share value that solves $V_{1j}(s, C_j, \varepsilon_1; \theta) = V_0(s, \varepsilon_0; \theta)$, then $C_j = C(s, \varepsilon; \theta)$ is the minimum willingness to accept (WTA) for adopting green practice $j$.

In practice, $V_1$ and $V_0$ are generally not separately identifiable, but their difference ($\Delta V = V_1 - V_0$) is. This difference can be expressed in a probabilistic framework as

$$(1) \quad \Pr\{\text{response is "yes"}\} = \Pr\{A_j \geq C_j(\cdot)\} = \Pr\{V_1 \geq V_0\} = \Pr\{\Delta V \geq 0\}$$

and hence the parameters necessary to calculate $C_j$ can be estimated through maximum likelihood. The probability of farmer adoption at $C_j$ is $F_\varepsilon[\Delta V(C_j)]$, where $F_\varepsilon$ is a cumulative density function (CDF). Given that $\pi_{1j}$ and $\pi_0$, as well as any nonfinancial motivations for adoption, are unlikely to be known to the researcher, survey approaches (such as those that explicitly ask the farmer whether she would adopt for a given incentive payment $A$) are needed to estimate the parameters of $F_\varepsilon$ (Cooper, Cooper and Keim, Khanna). Now suppose that three BMPs can be cost-shared, and suppose that the farmer answers "no" to cost share offers for practices 1 and 3, but "yes" to practice 2. Extending equation (1) and denoting the joint density by $g_C$,

$$(2) \quad \Pr\{\text{"no" to 1 and 3, "yes" to 2}\} = \Pr\{C_1 \geq A_1, C_2 \leq A_2, \text{ and } C_3 \geq A_3\} = \int_{A_1}^{\infty}\int_{0}^{A_2}\int_{A_3}^{\infty} g_C(C_1, C_2, C_3)\, dc_1\, dc_2\, dc_3.$$

According to Hanemann and Kanninen, but applied to the WTA case, let $G_C(C_1, \ldots, C_J)$ be the joint distribution function associated with the density $g_C(C_1, \ldots, C_J)$, and let $G_{(j)}(C_1, \ldots, C_J)$ denote the partial derivative of this joint distribution with respect to the $j$th argument: $G_{(j)}(C_1, \ldots, C_J) \equiv \partial G_C(C_1, \ldots, C_J)/\partial C_j$. Then, an equivalent way to express equation (2) is (Hanemann and Kanninen)

$$(3) \quad F_2 = \Pr\{\text{"no" to 1 and 3, "yes" to 2}\} = \Pr\{C_1 \geq A_1, C_2 \leq A_2, \text{ and } C_3 \geq A_3\} = \int_{0}^{A_2} G_{(2)}(A_1, C_2, A_3)\, dc_2.$$

Assuming the $\Delta V(C_j)$ are distributed normally but are correlated through the error terms, then the multivariate distribution needs to account for the correlations, where the $(J \times 1)$ vector $\mathbf{\Delta V}$ is distributed as $\mathbf{\Delta V} \sim F(\mu^1, \mu^2, \mu^3, \ldots, \mu^J; \Sigma)$, where $\Sigma$ is the $(J \times J)$ correlation matrix between the practices. The next section presents the empirical model for estimating the parameters of such a distribution.

## Econometric Model

Assume that $N$ farmers choose among a set of $J$ practices. The farmer's RUM associated with

[1] In theory, the farmer's utility maximization process is a combination of the discrete decision to adopt as well as the continuous decision of how many acres to adopt the BMPs on. We address only on the former, which was the main focus of our survey questions.

the incentive payment offer to adopt the BMP is [2]

$$(4)\qquad \Delta V_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta}_j + \varepsilon_{ij} \qquad (j = 1, \ldots, J;\ i = 1, \ldots, N)$$

where $\mathbf{x}_{ij}$ is a vector of explanatory variables for choice $j$ for farmer $i$ and $\boldsymbol{\beta}_j$ the vector of coefficients associated with choice $j$. The MNP model assumes that the correlations between the practices occur through the error terms in the equations, which are distributed as $\varepsilon_i \equiv (\varepsilon_{i1}, \ldots, \varepsilon_{iJ})' \sim \text{IIDN}(0, \Sigma),\ \Sigma = \lfloor \sigma_{ij} \rfloor$. The MNP log-likelihood function to be estimated is an expanded version of the bivariate model (Greene):

$$(5)\qquad L(\beta, \Sigma) = \sum_{i=1}^{N} \log F(\omega_i, \Sigma^*)$$

where $\omega_i \equiv (q_{i1} * \Delta V_{i1}, \ldots, q_{iJ} * \Delta V_{iJ})'$ and, for the model for current nonusers only, $x_{ij} = \{x_{ij1} * r_{ij}, \ldots, x_{ijP} * r_{ij}\}$, where dummy variable $r_{ij} = 1$ if $i$ is a current nonuser of $j$, and 0 otherwise, $p = 1, \ldots, P$ variables, and

$$q_{ij} = \begin{cases} 1 \text{ if farmer } i \text{ adopts practice } j \\ -1 \text{ if farmer } i \text{ does not adopt practice } j \end{cases}$$

and $\Sigma^* = T_i \Sigma T_i$, where $T_i$ is a $J \times J$ diagonal matrix with $T_i \equiv (q_{i1}, \ldots, q_{iJ})'$ on the diagonal, and where the unrestricted $J \times J$ covariance matrix has $(J - 1) \times J$ free elements (after imposing symmetry conditions).

Leaving out the subscript $i$, the multivariate normal density function in equation (5) is

$$(6)\qquad F(\vec{w}, \Sigma^*) = \frac{1}{\sqrt{|\Sigma^*|(2\pi)^J}} \int_{-\infty}^{w_1} \int_{-\infty}^{w_2} \cdots \times \int_{-\infty}^{w_J} e^{-\frac{1}{2}\theta' \Sigma^{*-1} \theta}\, d\theta$$

where $w_j = (\omega_j - \mu_j)/\sigma_j$, $\sigma_j = 1$, $\mu_j = 0$ .

As noted earlier, the computational intractability of the MVN density in equation (6) accounts for the fact that it is rarely used in dimensions higher than $J = 2$ (bivariate), or increasingly, $J = 3$ (trivariate). The traditional numerical quadrature methods for calculating $F(\cdot)$ tend not only to be unacceptably slow in more than three or four dimensions, they also suffer from serious shortcoming in numerical accuracy as $J$ increases (e.g., Horowitz, Sparmon, and Daganzo). An alternative to the quadrature methods, namely the Monte Carlo methods, is necessary to estimate this CDF. Simulation of standard normal variables is a well-studied problem (see Stern for an overview of simulation-based methods), although applications in the applied economics area exist but are rare (e.g., the trivariate model in Dorfman). To some extent this state is due to desktop computers only recently having the computational speed to perform this analysis and to a lack of available software. For this article, the GHK (Geweke–Hajivassiliou–Kean) importance sampling technique (Stern) and a similar technique proposed by Genz were both tried and they gave similar results.

Since the Monte Carlo simulator can approximate the probabilities of the MVN density in equation (6) to any desired degree of accuracy, the corresponding simulated maximum likelihood estimate (SMLE) based on the simulated MVN can approximate the MLE estimator (Hajivassiliou, McFadden, and Ruud). For the results to be consistent, the number of simulations must increase with the sample size at a sufficiently rapid rate (Newey and McFadden). One hundred repetitions are used here (as suggested by Geweke, Kean, and Runkle for their simulated MNP model).

A potential drawback of the econometric model presented above (or any other multivariate probit applications that the authors are aware of) is that it could potentially be subject to biases associated with incorrect specifications of the functional form of the RUM and of the normality assumption. We extend Creel and Loomis' semi-nonparametric (SNP) distribution-free approach for the univariate discrete choice case to our multivariate discrete choice model. This approach uses the Fourier functional form (e.g., Fenton and Gallant) as a substitute for the parametric functional form of the RUM in equation (4). The Fourier functional form is one of the few functional forms known to have Sobolev flexibility, which means that the difference between a function $\Delta V(\mathbf{x}, \theta)$ and the true function $f(\mathbf{x})$ can be made arbitrarily small for any value of $\mathbf{x}$ as the sample size becomes large (Gallant).

[2] A full MNP model would have variables in the RUMs in equation (4) whose values vary across the $J$ choices. While such variables are possible for some datasets, such as those used in recreational site choice, such variables are unlikely to be available to researchers modeling the farmer's technology adoption process. However, convergence of a MNP model with such variables generally requires restrictions on the correlation matrix, such as normalizing it along one row.

Creel and Loomis' specification of $\Delta V$ modified for the MNP model is:

$$(7)\quad \Delta V_F(\mathbf{x}_{ij}, \boldsymbol{\theta}_{kj}) = \mathbf{x}'_{ij}\boldsymbol{\beta}_j + \sum_{m=1}^{M}\sum_{l=1}^{L}(v_{lmj}\cos[l\mathrm{r}'_{mj}s(\mathbf{x}_{ij})] - w_{lmj}\sin[l\mathbf{r}'_{mji}s(\mathbf{x}_{ij})])$$

where the $p \times 1$ vector $\mathbf{x}_{ij}$ contains all arguments of the utility difference model, $k$ is the number of coefficients in $\boldsymbol{\theta}_j$, which consists of the $\boldsymbol{\beta}_j$, $v_{lmj}$, and $w_{lmj}$ are the coefficients to be estimated, $M$ and $L$ are positive integers, and $\mathbf{r}_{\mathrm{mj}}$ is a $p \times 1$ vector of positive and negative integers that forms indices in the conditioning variables and that determine which combinations of variables in $\mathbf{x}_{ij}$ form each of the transformed variables, and $j = 1, \ldots, J$ BMPs.[3] The integer $m$ is the sum of the absolute value of the elements in the multi-indexes in vector $\mathbf{r}_{\mathrm{m}}$ and $L$ is the order of the transformation, and is basically the number of inner loop transformations of $\mathbf{x}_i$ (ignoring the $j$ subscript for clarity of exposition). For example, if $\mathbf{x}_i$ contains three variables and $M = L = 1$, then the $\mathbf{r}_m$ vectors are (1,0,0), (0,1,0), and (0,0,1), resulting in $k = 9$ (not counting the constant). The $p \times 1$ function $s(\mathbf{x}_i)$ prevents periodicity in the model by rescaling $\mathbf{x}_i$ so that it falls in the range $[0, 2\pi - 0.000001]$ (Gallant). This rescaling of each element in $\mathbf{x}_i$ is achieved by subtracting from each element in $\mathbf{x}_i$ its minimum value (from across the sample), then dividing this difference by the maximum value (from across the sample), and then multiplying the resulting value by $[2\pi - 0.000001]$. For example, if bid is the only explanatory variable, then $\mathbf{r}_{\mathrm{m}}$ is a $(1 \times 1)$ unit vector and max $(M)$ equals 1. If furthermore, $M = L$ and bid offer $A_j$ has more than three unique values, then

$$(8)\quad \Delta V(A_j, \theta_{kj}) = \alpha_j + \delta_j A_j + \delta_{jv}\cos s(A_j) + \delta_{wj}\sin s(A_j).$$

If a variable has only three unique values, then only the $v$ or $w$ transformation may be performed. In practice, the level of transformation in equation (8) generally adds sufficient flexibility to the model. To apply this approach to the multivariate discrete model, the $\Delta V_{ij} = x'_{ij}\beta_j$ terms in the MLE in equation (5) are replaced with those in equation (8). The SNP functional form for the RUM adds substantial flexibility to the model, and if the assumption of the normal distribution is inappropriate, such an effect should be seen through significant coefficients on the higher-ordered terms, noting that the parametric model (equation (4)) is nested in the SNP model (equation (7)). Of course, statistical differences between the SNP and the parametric-based MNP approaches may be due to incorrect specification of the functional form or the density function, but these cannot be separably identified.

## Numerical Illustration

The data used for the numerical illustration are taken from a data collection and modeling effort undertaken jointly by the Natural Resource Conservation Service (NRCS), the Economic Research Service (ERS), the U.S. Geological Survey (USGS), and the National Agricultural Statistical Service (NASS).[4] Data on cropping and tillage practices and input management were obtained from comprehensive field and farm-level surveys of about 1,000 farmers apiece for cropping practices in each of four critical watershed regions. None of the respondents indicated that they were enrolled in WQIP (the EQIP-like program in existence at the time of the survey). Table 1 describes the five BMPs that were addressed in the survey instrument. Table 2 presents the frequency of occurrence of the actual adoption of various BMP combinations in the sample. The choice of bundles is clearly nonrandom, as one would expect. Of the thirty-two possible combinations (including the null set), over 92% of the farmers are accounted for by eleven combinations. However, table 2 tells us nothing about what the socially optimal bundles are; the farmer's choice of bundle is largely a business decision, while the socially optimal choice balances economic and environmental costs and benefits.

Here we focus on the hypothetical adoption decision by current nonusers of the practice, with the Appendix presenting the analysis of the actual (current) adoption decision. In the survey, current nonusers of each practice (i.e., those who said that they did not currently use the practice) were asked if they would adopt

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[3] In addition to appending $x\beta$ to the Fourier series in equation (7), Gallant suggests appending quadratic terms when modeling nonperiodic functions. Our experiments suggest that inclusion of the quadratic terms in the regressions had little impact on the WTA estimates. Hence, we leave them out for the sake of efficiency.

[4] As the data are discussed in detail in Cooper and in Cooper and Keim, for brevity and to avoid repetition, we do not discuss the data in detail here.

**Table 1. Descriptions of the Farm Management Practices Presented in the Survey Instrument**

| | |
|---|---|
| Conservation Tillage (CONTILL) | Tillage system in which at least 30% of the soil surface is covered by plant residue after planting to reduce soil erosion by water; or where soil erosion by wind is the primary concern, at least 1,000 pounds per acre of flat small grain residue-equivalent are on the surface during the critical erosion period. |
| Integrated Pest Management (IPM) | Pest control strategy based on the determination of an economic threshold that indicates when a pest population is approaching the level at which control measures are necessary to prevent a decline in net returns. This can include scouting, biological controls and cultural controls. |
| Legume Crediting (LEGCR) | Nutrient management practice involving the estimation of the amount of nitrogen available for crops from previous legumes (e.g. alfalfa, clover, cover crops, etc.) and reducing the application rate of commercial fertilizers accordingly. |
| Manure Testing (MANTST) | Nutrient management practice which accounts for the amount of nutrients available for crops from applying livestock or poultry manure and reducing the application rate of commercial fertilizer accordingly. |
| Soil Moisture Testing (SMTST) | Irrigation water management practice in which tensiometers or water table monitoring wells are used to estimate the amount of water available from subsurface sources. |

**Table 2. Frequency of Occurrence of Actual Adoption of Various BMP Combinations in the Sample ("1" = BMP is Used; "0" = BMP is Not Used)**

| CONTILL | IPM | LEGCR | MANTST | SMTST | Frequency (%) |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 36.66 |
| 0 | 0 | 0 | 0 | 0 | 15.32 |
| 1 | 0 | 1 | 0 | 0 | 9.41 |
| 1 | 1 | 0 | 0 | 0 | 8.92 |
| 1 | 1 | 1 | 0 | 0 | 7.37 |
| 0 | 1 | 0 | 0 | 0 | 3.78 |
| 1 | 0 | 0 | 0 | 1 | 3.30 |
| 1 | 1 | 1 | 1 | 0 | 2.33 |
| 0 | 0 | 1 | 0 | 0 | 1.94 |
| 1 | 1 | 1 | 0 | 1 | 1.94 |
| 1 | 0 | 1 | 1 | 0 | 1.36 |
| Total use of each BMP in the sample (%) | | | | | |
| 74.88 | 29.78 | 27.74 | 7.57 | 9.70 | |

Notes: Only bundles with a reported frequency of 1% or greater are listed above. The bundles above represent those reported by 92.33% of the farmers in the sample. Sample size = 1,031. Only 0.87% of sample reported using all five practices.

the BMP with an incentive payment of $[X] per acre, a value that varied across the respondents in the range of $2 to $24. For any one respondent, however, to avoid anchoring biases across the responses, the offered bid was the same for each practice. Each of the five adoption questions was placed on the same page so that the respondent was concurrently aware of all five. As the bid variable (cost share) is uncorrelated with any other variables by the design of the survey instrument, it is the only relevant variable for examining the relationship between the bid and probability of acceptance and for calculating the mean benefit for the sample (Mcfadden), with additional explanatory variables serving largely to stratify the sample. For brevity then, we present the results for the regressions with just the bid variable.[5] The Appendix presents econometric results that relate a number of explanatory variables to the actual decision to adopt, i.e., the analysis of adoption where $A_j = \$0$.

[5] Results for the SNP model with multiple regressors are too lengthy to present here, but are available upon request from the authors.

As only the adoption decision of current nonusers of the BMPs is analyzed in the main body of this article, the estimated probabilities are conditional on nonadoption, i.e., Pr{Farmer accepts bid $A$ in turn for adoption of the BMP | farmer is not current user of the BMP}. This conditional probability is appropriate to this article's policy goal of examining the USDA's Environmental Quality Incentives Program (EQIP). This is because EQIP offers cost shares only to current nonusers of the BMPs. Hence, the policy-relevant density function for EQIP is Pr{Farmer accepts bid $A$ in turn for adoption of the BMP | farmer is not current user of the BMP}, and not the unconditional Pr{Farmer accepts bid $A$ in turn for adoption of the BMP}. In other words, concern over potential sample selection bias in examining only current nonusers is eliminated if our policy interest is EQIP. In fact, for the purposes of EQIP, we are only interested in the subsample of farmers who do not currently use the BMPs.

The likelihood function and maximization routines were programmed by the author in GAUSS.[6] Regression results are presented in table 3 (correlation coefficients are presented in table A.3 in the Appendix). The second and third columns in table 3 are the results using the parametric RUM specification and the last two columns represent the SNP RUM model results. The "restricted" columns present the results of the model where the off-diagonal terms in the correlation matrix of the five practices are restricted to equal zero. In this case, the estimated coefficients and standard errors are equivalent to those from separate probit regressions for each practice. The coefficient of the offer amount (BID) is of the expected sign and significant to at least the 10% level, and for most cases, the 1% level, except for those for CONTILL in the SNP models, perhaps due to some collinearity in the case of BID with the higher-order terms. In fact, the bid offer for CONTILL was \$2 per acre lower, and hence, the bid range narrower, than for the other practices (which all had the same bid offers), as pretesting of the survey suggested that farmers expected conservation tillage to receive a lower cost share than the other practices. Note that the only two cases where one of the higher-order terms is significant is that on "cos $s$(BID)" and "sin $s$(BID)" in the restricted case for the adoption of LEGCR and SMTST, respectively.

As the restricted model (i.e., each adoption function is independent of the other) is nested within the unrestricted model for both the parametric and SNP cases, a likelihood ratio test, namely $LR = -2(\ln L_r - \ln L_u)$, can be used to test the null hypothesis that farmers consider each BMP adoption decision as an independent one. Given the log-likelihood values at the bottom of table 3, this hypothesis is not accepted for any reasonable level of significance in either the parametric or SNP cases. As the unrestricted RUM is nested within the unrestricted SNP RUM, a likelihood ratio test can be used to test the null hypothesis that the BMPs are distributed normally with a linear RUM. This hypothesis cannot be accepted either, but the critical value of 15.14 is much lower than those comparing the restricted and unrestricted models. In fact, a simple visual comparison of the coefficients on BID between the restricted (unrestricted) parametric and restricted (unrestricted) SNP models indicates no major differences.

The Appendix provides the results for the MNP analysis of current users versus nonusers of the BMPs. Two basic conclusions follow from this analysis. One is that none of the available variables stand out as an important predictor of current use (the SNP specification was not practical with this larger dataset).[7] But most significant for this article is that the restricted MNP model is rejected at any reasonable level of significance, given that the log-likelihood for the unrestricted MNP model of −2176, and the likelihood value for the (nested) restricted model (not shown) is −2223. This result can be interpreted as empirical evidence that the correct decision was made for the hypothetical survey questions to make the respondent concurrently aware of each of the possible BMPs.

For the analysis of hypothetical adoption, the correlation coefficients between the practices are significant to at least the 1% level as well, regardless of whether they are estimated for the parametric or SNP regressions (Appendix table A.3, second and third set of numbers). The correlation coefficients for the

[6] The only commercially available program that the authors are aware of that performs the MNP using the simulated normal is an optional package in Limdep. However, the authors found that modeling the data on the five BMPs with the commercially available software was too computationally burdensome to be practical.

[7] The decision on which variables to include in the regressions for each of the practices was based on whether or not the variables appear justified from a farm management standpoint.

**Table 3. Restricted and Unrestricted Multinomial Probit Regression Results (Parametric and Semi-Nonparametric RUMs)**

| | | Coefficient Estimates (Coefficient Estimates/Standard Error) | | | |
|---|---|---|---|---|---|
| | | Parametric | | SNP | |
| Practices | Variables | Restricted | Unrestricted | Restricted | Unrestricted |
| CONTILL | CONST | −0.7815 | −0.8199 | −0.7783 | −0.7520 |
| | | −(4.252) | −(5.75) | −(2.445) | −(2.962) |
| | BID | 0.0221 | 0.0187 | 0.0217 | 0.0150 |
| | | (1.834) | (1.838) | (1.024) | (0.834) |
| | sin *s*(BID) | | | 0.0217 | 0.0738 |
| | | | | (.287) | (1.427) |
| | cos *s*(BID) | | | 0.0106 | 0.0179 |
| | | | | (0.105) | (0.239) |
| IPM | CONST | −1.0979 | −1.0729 | −1.1157 | −1.0971 |
| | | −(10.61) | −(12.11) | −(7.488) | −(8.11) |
| | BID | 0.0325 | 0.0256 | 0.0344 | 0.0273 |
| | | (3.97) | (3.77) | (2.839) | (2.542) |
| | sin *s*(BID) | | | −0.0209 | 0.0004 |
| | | | | −(0.537) | (0.011) |
| | cos *s*(BID) | | | 0.0037 | 0.0087 |
| | | | | (0.069) | (0.212) |
| LEGCR | CONST | −1.7462 | −1.4099 | −1.5381 | −1.3265 |
| | | −(10.93) | −(15.46) | −(7.452) | −(10.86) |
| | BID | 0.0469 | 0.0301 | 0.0283 | 0.0234 |
| | | (4.118) | (4.682) | (1.678) | (2.533) |
| | sin *s*(BID) | | | 0.0460 | −0.0069 |
| | | | | (0.744) | −(0.215) |
| | cos *s*(BID) | | | −0.1208 | −0.0646 |
| | | | | −(1.683) | −(1.156) |
| MANTST | CONST | −1.5757 | −1.3729 | −1.6911 | −1.4134 |
| | | −(12.15) | −(13.97) | −(8.562) | −(10.77) |
| | BID | 0.0334 | 0.0226 | 0.0442 | 0.0264 |
| | | (3.445) | (3.033) | (2.823) | (2.53) |
| | sin *s*(BID) | | | −0.0817 | −0.0482 |
| | | | | (1.634) | −(1.382) |
| | cos *s*(BID) | | | 0.0233 | 0.0003 |
| | | | | (0.361) | (0.007) |
| SMTST | CONST | −1.4575 | −1.3253 | −1.4840 | −1.3403 |
| | | −(12.32) | −(15.79) | −(9.445) | −(10.1) |
| | BID | 0.0327 | 0.0239 | 0.0311 | 0.0229 |
| | | (3.661) | (3.938) | (2.496) | (2.21) |
| | sin *s*(BID) | | | 0.0802 | 0.0364 |
| | | | | (1.726) | (.912) |
| | cos *s*(BID) | | | 0.0339 | 0.0115 |
| | | | | (0.547) | (0.238) |
| | Ln *L* | −2511.60 | −2099.42 | −2505.85 | −2106.99 |

Note: The unrestricted multinomial probit model estimates the correlation between the five practices. The restricted model assumes the cross practice correlations are zero, and hence, its coefficients and standard errors are the same as in individual standard probit results for each practice. For each practice, the dependent variable = "1" if the farmer agrees to adopt the practice at the offered bid (cost share), and "0" otherwise.
Random Utility Model = RUM.

regressions predicting current use (first set of numbers in table A.3) tend to be less significant than the correlations between the hypothetical use results. This difference in significance is to be expected; whether or not the farmer is a current user of the BMPs is a result of an evolutionary process, while the hypothetical adoption decisions are made over a bundle

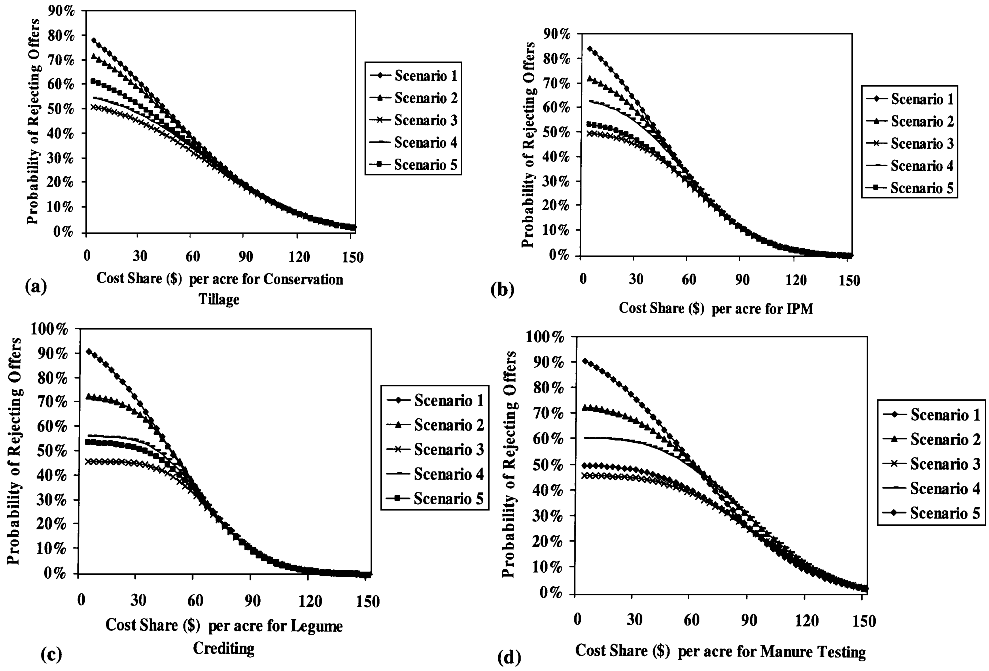


**Figure 1. Probability as a function of the cost share offer**

of practices offered to the farmer at one point in time in a survey instrument.[8]

Next, given that the restricted correlation model is not accepted (i.e., the BMP adoption decisions are not independent across BMPs), we turn to an evaluation of how the unrestricted MVN results can be used for the analysis of bundling. The basic value of the multivariate analysis is that it allows us to calculate the joint probabilities as a function of the incentive payments. Figures 1(a)–(d) provide examples of how the joint probability changes as a function of the incentive payment offers for four of the five BMPs analyzed here, i.e., the curves represent $\partial G_C(C_1, \ldots, C_J)/\partial C_j$ calculated across a wide range of cost share offers. For example, figure 1(a) plots the probability of nonacceptance of the conservation tillage cost share as a function of the cost share offer amount, given the value of the cost share offers for the other four BMPs. In figure 1(a), four scenarios (numbers 2–5) with different fixed offers for BMPs other than CONTILL are presented. For comparison, scenario 1 is the predicted probability for the standard univariate normal density function that does not explicitly account for the other bid offers.

Given the estimates of the CDFs generated from the analysis of discrete responses in the figures, the question that may arise is how to summarize these distributions of WTA for practical purposes. In the discrete-choice contingent valuation (CV) literature, the most common summary statistic is the mean of the estimated WTP or WTA distribution. Given the estimated coefficients from the multivariate probit regression, it is possible to calculate measures of conditional mean WTA. Hanemann notes that in the case where the benefit measure $C_R$ is restricted to the nonnegative range, its mean value can be found using the following formula for the mean of a random variable:

$$(9) \qquad C_R = \int_0^\infty F(C)\,dc$$

where $F(C) = F[-\Delta v(\mathbf{s}, C, \boldsymbol{\theta})]$ is the cumulative density function for WTP.[9,10] Here we present a new application in which the mean of the benefit measure for one good is calculated conditional on the bid offers made for

[8] An EQIP contract application is submitted at a particular point in time, when the proposed practices have not yet been adopted. The farmer is paid per year for each of the practices he agrees to adopt over the life of the contract.

[9] For this article, we are interested in comparisons of $E$(WTA) between the scenarios and not what the ideal benefit measure should be. For a discussion of the pros and cons of various benefit measures and issues of consistency of the estimated distribution with the benefit measure, see Hanemann and Kanninen.

[10] For WTP, the integral is taken over $1 - F(i)$, where $F(C) = F[\Delta v(s, C, \theta)]$.

other goods, an application made possible by the estimation of the multivariate normal CDF. Given a five-dimensional version of the multivariate CDF in equations (3) and (6), one can take the integral under $F$ with respect to one of the BMPs, thereby yielding a mean WTA for that BMP, conditional on the cost share offer amounts for the other BMPs. For example, for BMP $j = 2$ the mean WTA, $C_{R(2)}$, is

$$(10) \quad C_{R(2)} = \int_0^\infty F_{(2)}(A_1, C_2, A_3, A_4, A_5)\, dc_2.$$

In other words, equation (10) corresponds to the area under the curves in figures 1(a)–(d). Of course, given that a numerical approach is used to calculate the multivariate CDF, the mean value must also be calculated numerically. The lower right-hand corner of each figure presents the mean WTA values for each scenario, with the value associated with scenario 1 calculated using equation (9) and the values associated with scenarios 2 through 5 calculated using appropriate variations of equation (10).

In figures 1(a)–(d), the probability functions and mean WTA values differ little for scenarios 1 and 2, with the latter being consistently lower, although little perhaps can be said of this comparison as the results are generated from two different density function assumptions. Larger differences tend to occur between scenario 2 and the other joint-density scenarios (scenarios 3 through 5 in each figure). As is expected, the lowest minimum WTA in each figure is associated with scenario 3, the one in which all the BMPs except the one in question (e.g., CONTILL in figure 1(a)) are offered at a cost share of \$30 per acre. In other words, given that adoption of the practices is positively correlated (table A.3), one would expect that the more a farmer is offered to adopt a set of related practices, the less she will be willing to accept for the practice in question. Hence, for comparisons of scenarios 2 through 5, WTA should be highest under 2 and lowest under 3. This relationship holds for each of the four figures.

However, what is interesting from the standpoint of bundling the BMPs is that only one or two of the BMPs in scenario 3 in each figure may be driving much of the reduction in WTA over scenarios 2, 4, and 5. First take figure 1(a). In this figure, WTA under scenario 4 is not much higher than under scenario 3 even though only two of the other costs are being offered at nonzero cost shares. In fact, as shown in table 2, the bundle {CONTILL, IPM, LEGCR} in scenario 4 is used by 7.37% of the actual users, while only 0.19% use the bundle {CONTILL, MANTST, SMTST} in scenario 5.[11] In figure 1(b), the WTA for IPM in conjunction with CONTILL and SMTST cost shares at \$30 (scenario 5) was almost as low as that with the four BMPs being offered at \$30 in scenario 3 (scenario 3). For figure 1(c), no pairs of BMPs offered at \$30 in conjunction with LEGCR seemed to offer the bulk of the decrease in WTA associated with moving from scenario 2 to 3. In figure 1(d) however, offering CONTILL and SMTST at \$30 (scenario 5) yielded a WTA for MANTST almost as low as that for scenario 3.

## Conclusion

This article develops an econometric model based on the multivariate normal distribution that identifies producer tendencies to bundle types of management practices that may be covered under an incentive payment system. Identifying producer tendencies to bundle these types of practices may increase adoption and lower the costs of voluntary adoption programs. Although the scenario examined here relies on payments to encourage adoption, identifying these producer tendencies can also lower the government's costs of voluntary adoption programs that rely on the dissemination of information to encourage adoption. Since a critical component of voluntary adoption is producer perceptions, as in the numerical illustration, identifying and packaging BMPs that are perceived to be jointly beneficial, or bundled, may increase adoption and lower the costs of the programs. Thus, jointly modeling the observed adoption data across the BMPs can indicate which practices should be bundled into composite practices.

Our model can be used to identify adoption costs in the currently less than ideal situation facing EQIP (and all similar programs), where the environmental benefits associated with BMP adoption are unquantified. However, research is perhaps moving in the direction of quantifying (if not monetizing) the environmental benefits of such practices, e.g., the

[11] Further breakdowns of scenario 4 could be used to test whether IPM or LEGCR are contributing most to reducing WTA from the level under scenario 2, but are not considered here for the sake of brevity, given that the target audience for the detailed information on the bundles are managers of the cost-sharing program, and perhaps not the general readership of this journal.

USGS' Sparrow model may be modified in the future to measure the impact on sediment and nutrient loadings in watersheds that are associated with such practices. Given our estimated model in conjunction with an environmental benefits model, benefit-cost trade-offs of BMP adoption can be assessed.

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## Appendix

*Econometric Results for the Analysis of Current Users versus Nonusers of the Best Management Practices*

**Table A.1. Definitions of the Explanatory Variables (Mean/Standard Error)**

| | |
|---|---|
| TACRE | Total acres operated (1123/2034). |
| EDUC | Formal education of operator (3.194/2.314). |
| EINDEX | Sheet and rill erosion index. |
| FLVALUE | Estimated market value per acre of land (1383/1023). |
| EXPER | Farm operator's years of experience (24.83/20.15). |
| BPWORK | Number of days annually operator worked off the farm (42.71/99.15). |
| NETINC | Operation's net farm income in 1991 (24620/26890). |
| TISTST | Tissue test performed in 1992 (dummy) (0.029/0.149). |
| CTILL | Conservation tillage used in 1992 (dummy) (0.174/0.457). |
| PESTM | Destroy crop residues for host free zones (dummy) (0.163/0.355). |
| ANIMAL | Farm type-beef, hogs, sheep (dummy) (0.207/0.522). |
| ROTATE | Grasses and legumes in rotation (dummy) (0.049/0.239). |
| MANURE | Manure applied to field (dummy) (0.147/0.430). |
| HEL | Highly erodible land (dummy) (0.174/0.457). |
| IA | Sample located in the Eastern Iowa or Illinois Basin Area (dummy) (0.729/0.721). |
| ALBR | Sample located in Albermarle-Pamlico Drainage Area (dummy) (0.088/0.209). |
| IDAHO | Sample located in the Upper Snake River Basin Area (dummy) (0.123/0.341). |

**Table A.2. Multinomial Probit Regression Results Predicting Actual BMP Use/Nonuse (Log-Likelihood = −2175.86)**

| | Coefficient Estimates (Coefficient Estimates/Standard Error) | | | | |
|---|---|---|---|---|---|
| Variables | CONTILL | IPM | LEGCR | MANTST | SMTST |
| CONST | −0.0005 | −0.7960 | −0.9896 | −1.5657 | −0.8799 |
| | −(.002) | −(3.123) | −(2.743) | −(2.934) | −(1.995) |
| EDUC | −0.0072 | 0.1713 | 0.0928 | 0.0444 | 0.0158 |
| | −(.198) | (4.973) | (2.838) | (.814) | (.226) |
| CTILL | 0.3638 | – | – | – | – |
| | (3.583) | | | | |
| TISTST | – | – | −0.1174 | −1.9290 | – |
| | | | −(.402) | −(2.107) | |
| HEL | −0.0665 | – | – | – | – |
| | −(.536) | | | | |
| EXPER | 0.0018 | −0.0027 | −0.0015 | −0.0064 | −0.0053 |
| | (.489) | −(.706) | −(.424) | −(1.034) | −(.736) |
| PESTM | −0.0046 | 0.3862 | – | – | – |
| | −(.032) | (2.998) | | | |
| ROTATE | 0.0442 | −0.0041 | 0.2687 | – | – |
| | (.196) | −(.018) | (1.5) | | |
| MANURE | −0.1153 | −0.1821 | 0.0957 | 0.3512 | – |
| | −(.954) | −(1.336) | (.828) | (2.167) | |
| ANIMAL | −0.0074 | −0.2869 | −0.0071 | 0.1424 | −0.2030 |
| | −(.062) | −(2.246) | −(.068) | (.868) | −(.86) |
| TACRE | 7.38E-06 | 5.66E-05 | −3.07E-06 | −1.85E-05 | 3.66E-05 |
| | (0.235) | (1.513) | −(0.088) | −(0.466) | (0.886) |
| FLVALUE | −2.46E-05 | 5.24E-05 | −0.0001 | −7.22E-05 | −1.86E-05 |
| | −(0.31) | (0.739) | −(1.636) | −(0.579) | −(0.137) |
| IA | 0.4343 | −0.0815 | 0.8586 | 0.7698 | −0.4328 |
| | (2.017) | −(0.398) | (2.862) | (1.792) | −(1.498) |
| ALBR | 0.4087 | −0.1323 | −0.3991 | −0.1349 | −1.6877 |
| | (1.478) | −(0.479) | −(1.113) | −(0.261) | −(4.01) |
| IDAHO | 0.2278 | −0.3957 | 0.5796 | 0.4910 | 0.2289 |
| | (0.917) | −(1.667) | (1.805) | (1.021) | (0.795) |
| BPWORK | −0.0002 | −0.0003 | −0.0008 | 0.0002 | −0.0004 |
| | −(0.4) | −(0.534) | −(1.541) | (0.218) | −(0.382) |
| NETINC | 1.02E-06 | 6.21E-07 | −3.23E-06 | −2.19E-06 | 7.53E-06 |
| | (0.394) | (0.286) | −(1.524) | −(0.655) | (1.772) |

Note: For each BMP, the dependent variable = "1" if the farmer currently uses the BMP and "0" otherwise.

**Table A.3. Estimates of Correlations Between the BMPs**

| Practices | CONTILL | IPM | LEGCR | MANTST | SMTST |
|---|---|---|---|---|---|
| Regression Predicting Actual BMP Use/Nonuse | | | | | |
| CONTILL | – | | | | |
| IPM | 0.123 (1.6) | – | | | |
| LEGCR | 0.202 (2.7) | 0.401 (7.2) | – | | |
| MANTST | 0.0451 (0.4) | 0.417 (5.2) | 0.531 (6.7) | – | |
| SMTST | 0.186 (1.8) | 0.204 (2.1) | 0.124 (1.3) | 0.305 (2.7) | – |
| Regression for the Hypothetical Adopters Only—Parametric | | | | | |
| CONTILL | – | | | | |
| IPM | 0.7379 (16.1) | – | | | |
| LEGCR | 0.7584 (17.7) | 0.8151 (22.4) | – | | |
| MANTST | 0.5295 (7.2) | 0.7341 (14.7) | 0.8936 (28.1) | – | |
| SMTST | 0.6052 (9.7) | 0.6700 (12.3) | 0.7857 (15.1) | 0.7649(16.9) | – |
| Regression for the Hypothetical Adopters Only—SNP | | | | | |
| CONTILL | – | | | | |
| IPM | 0.7400 (15.7) | – | | | |
| LEGCR | 0.7776 (18.2) | 0.8188 (22.5) | – | | |
| MANTST | 0.5545 (7.6) | 0.7508 (15.1) | 0.8957 (28.3) | – | |
| SMTST | 0.6120 (9.7) | 0.6722 (12.1) | 0.7906 (14.8) | 0.7749(17.4) | – |